Federated Learning for Edge Networks: Resource Optimization and Incentive Mechanism

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Abstract—Recent years have witnessed a rapid proliferation of smart Internet of Things (IoT) devices. IoT devices with intelligence require the use of effective machine learning paradigms. Federated learning can be a promising solution for enabling IoT-based smart applications. In this paper, we present the primary design aspects for enabling federated learning at network edge. We model the incentive-based interaction between a global server and participating devices for federated learning via a Stackelberg game to motivate the participation of the devices in the federated learning process. We present several open research challenges with their possible solutions. Finally, we provide an outlook on future research.

Index Terms—Federated learning, Internet of Things, Stackelberg game, edge networks.

I. INTRODUCTION

Recently, edge computing has gained significant interest due to its ability of extending cloud computing utilities and services to the network edge with low-latency. Numerous Internet of Things (IoT) applications such as augmented reality, autonomous driving, forest fire surveillance, industry 4.0, smart health-care, among others, require edge processing with low latency [1]. In such applications, the involved IoT end devices have stringent computational resource constraints. One way to provide those IoT edge devices with on-demand computing resources is by using a remote cloud. However, the inherent delay pertaining to end-to-end communications with a cloud server can lead to intolerable latency. Therefore, edge computing is a promising solution to enable latency-sensitive IoT applications by providing low-latency on-demand computing resources [2]. On the other hand, the data generated by end IoT devices offers an opportunity of using machine learning schemes to enable intelligent applications. Therefore,

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it is indispensable to use of machine learning at the edge to enable various smart applications.

Traditional machine learning use centralized training data at a data center which requires migrating of data from a massive number of geographically distributed smart IoT devices to a centralized location for training [3]. Storing user data at a centralized location of a third party raises serious privacy concerns. To cope with the limitation of not preserving the users' privacy in centralized learning, it is important to introduce distributed, edge-deployed learning algorithms such as federated learning [4]. Federated learning allows privacy preservation by avoiding use of centralized training [4]. An overview of how federated learning can enable IoT-based smart applications is presented in Fig. 1. Depending on how the global learning model is being operated, we can distinguish two categories of federated learning: Cloud-based federated learning and edge-based federated learning [5]. Edge-based federated learning involves a set of devices within close vicinity and computation of global learning model at edge server. On the other hand, a cloud-based federated learning model involves the computation of a global learning model at a cloud for IoT devices that are geographically distributed over a large area. Hereinafter, we consider only edge-based federated learning because of the prime role that it will play in tomorrow's wireless and IoT networks [1].

To benefit from the deployment of federated learning, it is important to address few technical challenges that include local device computational and communication resources optimization. In addition, there is a need for effective incentive mechanisms to motivate the participation of users in the learning of a global federated learning model. Several recent works have considered machine learning in enabling IoT-based smart applications [6]–[9]. The works presented in [6], [7] mostly rely on centralized machine learning solutions which can have limitations in terms of scalability as well as privacy-preservation. In [8], the authors studied a federated learning framework to provide efficient resource management at the network edge. The work in [8] presented building blocks, different neural network schemes, and key enablers of machine learning at network edge. However, the works in [8] and [9] do not discuss the important challenges pertaining to incentive design and network optimization under edge-based federated learning. Our key contributions include:

- We present the key design challenges and opportunities for implementation of federated learning in edge networks.
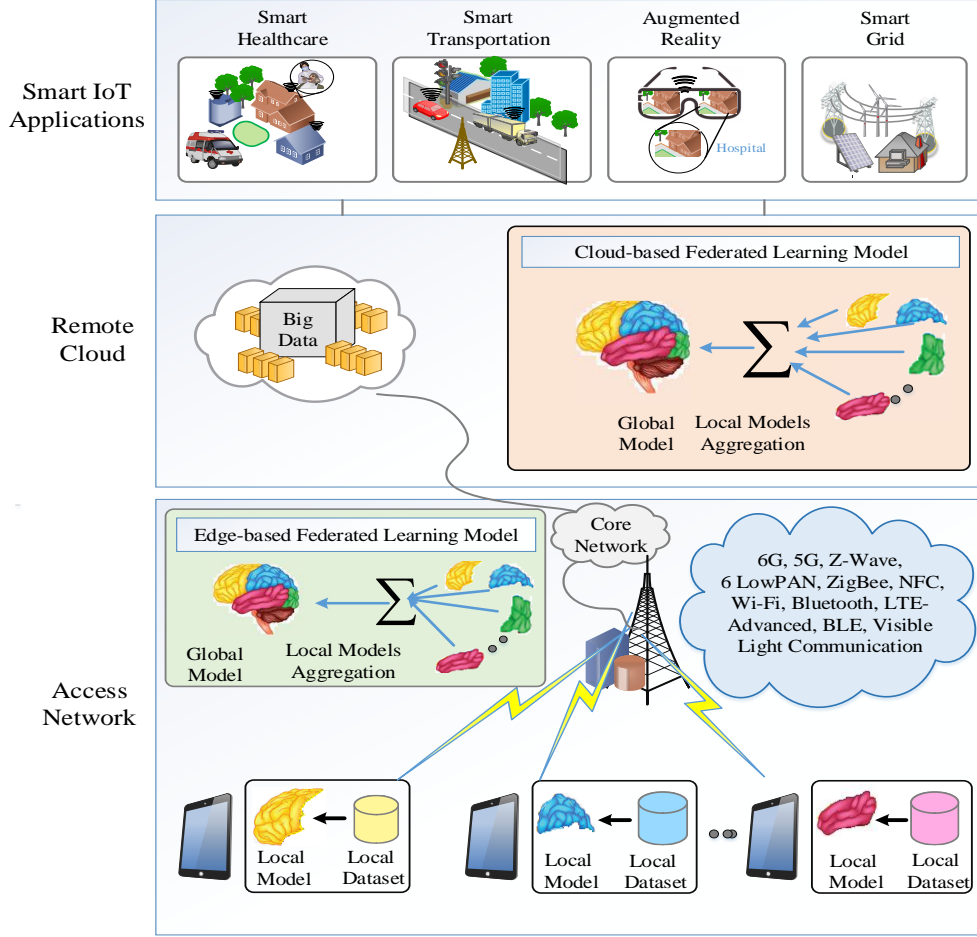- We propose a Stackelberg game-based approach to de-

Fig. 1: An overview of federated learning in enabling IoT-based smart applications

velop an incentive mechanism for federated learning. The Stackelberg game-based interaction enables the clients to strategically set the number of local iterations to maximize their utility. On the other hand, the base station (BS) uses the best response strategies of the users to maximize the performance of federated learning by solving its utility maximization problem. Here, the BS's utility can be modeled as a function of key performance metrics such as the number of global iterations and global accuracy level in the federated learning setting.

- Finally, we present some key open research challenges along with guidelines pertaining to federated learning in edge networks.

To the best of our knowledge, this is the first work to review resource optimization and incentive mechanism for federated learning over edge networks.

II. FEDERATED LEARNING AT THE EDGE: KEY DESIGN ASPECTS

A. Resource Optimization

Optimization of communication and computation resources is absolutely necessary to enable the main phases of federated learning, such as local computation, communication, and global computation. Computation resources can be either those of a local device or of an edge server, whereas communication resources are mainly radio resources of the access network. In the local computation phase, every selected device performs a local model update using its dataset in an iterative manner. The allocation of local device computational resources strongly depends on the device energy consumption, local learning time, and local learning accuracy. In addition, the heterogeneity of the local dataset sizes significantly affects the allocation of local computational resources. Device energy consumption and local learning time are strongly dependent on the CPU capability of the edge device. Increasing the device CPU frequency yields an increase in energy consumption and a decrease in learning time. Similarly, the local computational latency increases for a fixed frequency with an increase in local learning accuracy. Therefore, it is evident that here is a need to study the tradeoff between computation energy consumption, computational latency, learning time, and learning accuracy. On the other hand, the access network and core network resources must be allocated optimally in the communication phase [10].
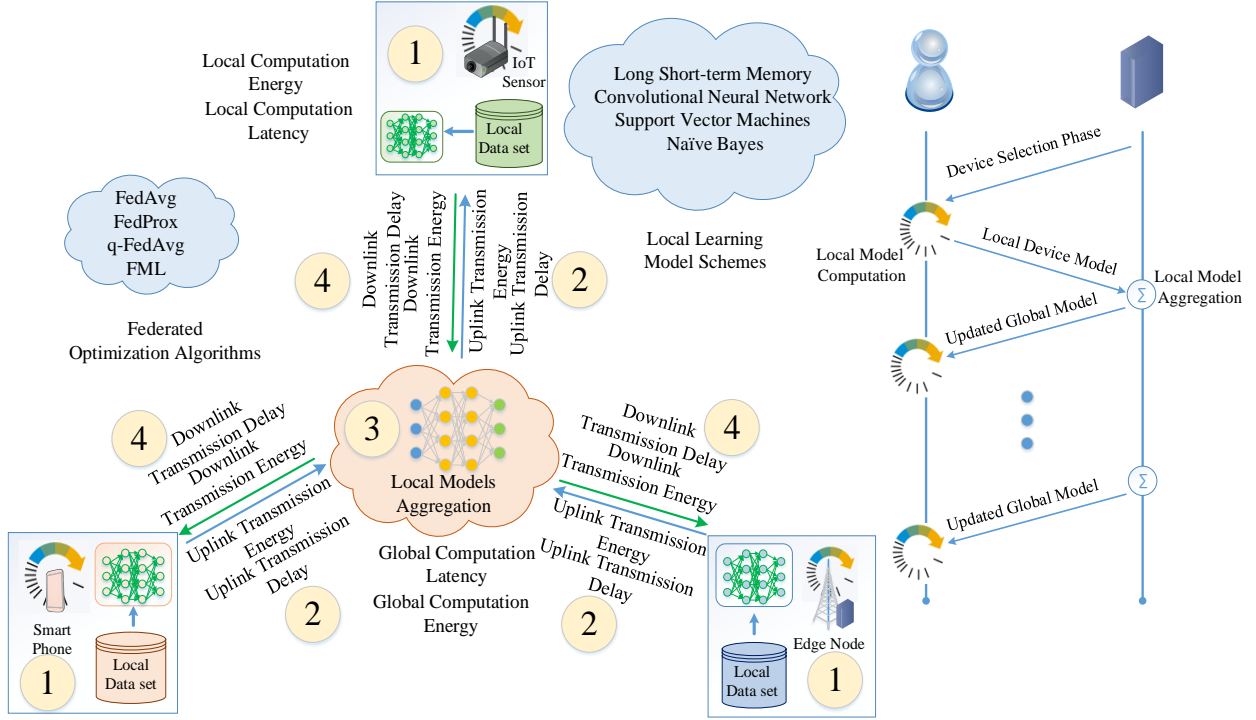
Fig. 2: Federated learning sequence diagram

B. Learning Algorithm Design

Federated learning involves the usage of local and global computation resources in addition to communication resources. Several machine learning techniques, such as long short-term memory, convolutional neural network, support vector machines, and Naive Bayes schemes can be used at each local device [3]. To enable federated learning, numerous optimization schemes, such as federated averaging (FedAvg) and FedProx can be used to train non-convex federated learning models [11]. FedProx is the modified version of FedAvg and it counts for statistical heterogeneity among users. FedAvg is based on running stochastic gradient descent (SGD) on a set of smart devices with statistical homogeneity to yield local model weights. Subsequently, an averaging of the local weights is performed at the edge computing server located at BS. FedProx has similar steps as FedAvg, but the difference lies in local device minimizing of objective function that considers the objective function of FedAvg with an additional proximal term which limits the impact of local device data non-independent and identically distributed (non-IID) on the global learning model. FedAvg does not guarantee theoretical convergence, while FedProx shows theoretical convergence.

In FedAvg and FedProx, all the devices are weighted equally in global federated learning model computation without considering fairness among devices. However, there exist significant variations in different devices nature (i.e., hardware variability). To address such fairness issues, a so-called q-FedAvg algorithm has been recently proposed. The idea of q-FedAvg is to give higher weights to the devices with poor performance by modifying the objective function of the typical FedAvg algorithm. To introduce potential fairness and reduce training accuracy variance, the local devices having a high empirical loss (local loss function) are emphasized by setting large values of q in the q-FedAvg. Specifically, the value of q determines the amount of fairness, greater that value of q more will be the fairness and vice versa. On the other hand, an adaptive control scheme has been proposed regarding the adaptation of global aggregation frequency for federated learning [5]. Moreover, the adaptive control scheme offers a desirable tradeoff between global model aggregation and local model update to minimize the loss function with resource budget constraint. All of the above discussed methods are used for a single task global federated learning model. We can use a multi-task learning model for multiple tasks, whose data is distributed among multiple edge nodes in a federated learning setting. In [12], federated multi-task learning (FML) has been proposed while considering fault tolerance and joint optimization of both communication and computational resources.

C. Incentive Mechanism Design

In addition to resource optimization and learning algorithm design, a set of devices involved in the training of a global federated learning model must be given proper incentives to ensure the trustworthiness of their participation in federated learning. Incentives are possible in different forms, such as user-defined utility and money-based rewards. Several frameworks such as game theory, matching theory, and auction theory can be used in the design of incentive mechanisms for federated learning [13], [14]. For instance, consider an incentive mechanism based on game theory in which an

edge server and and edge users act as a set of players. The edge server announces a reward as an incentive to the participating nodes while maximizing its benefits in terms of improving global federated learning model accuracy. On the other hand, the edge users try to maximize their individual utilities to improve their benefit. In this regard, utility can, for example, be defined as the improvement of local learning model accuracy within the allowed communication time during the training process. An improvement in the local learning model accuracy of the end-user increases its incentive from the edge server and vice versa. This process of incentive-based sharing of model parameters is continued until convergence to some global model accuracy level.

III. Incentive Based Federated Learning Over Edge Networks

A. System Model

Consider a multi-user system comprised of a BS and a set of user devices with non-IID and heterogeneous data sizes. Enabling federated learning over such edge networks involves the use of local device computational resources, cloud computational resources, and communication resources that must be optimally exploited. In a typical federated learning environment, the participating user equipment (UE) have to iterate over their local data with possibly non-IID and un-balanced nature, to train a global model. However, UEs are generally reluctant to participate in federated learning due to limited computing resources and limited communication resources [10]. Thus, enabling federated learning requires some careful design considerations that include:

- First of all to motivate UEs for participation, it is necessary to model the economic interaction between the BS and the UEs. Within each global iteration, the BS can offer a reward rate (e.g., $/iterations) to the UEs for their selection of the optimal local iteration strategy (i.e., CPU-frequency cycle) that can minimize the overall energy consumption of federated learning, with a minimal learning time.
- The set of resource-constrained UEs involved in federated learning has numerous heterogeneous parameters: Computational capacity, training data size, and channel conditions. This heterogeneity of UEs significantly affects the local learning model computation time for a certain fixed local model accuracy level. To compute the local learning model within fixed allowed time for resource-constrained UEs with heterogeneous parameters, the local learning model accuracy will be different for different UEs. Therefore, it is necessary to tackle the challenge of heterogeneous local learning model accuracy of the participating UEs for synchronous federated learning.

B. Stackelberg Game Solution

The BS employs an incentive mechanism for motivating the UEs to participate in training of a global federated learning model. However, heterogeneous UEs have different computational and communication costs needed to train a global model. Therefore, they expect different reward rates to perform optimally in a federated learning setting. On the other hand, the BS seeks to minimize the learning time while maximizing the accuracy level of the learning model. Thus, this complex interaction between the BS and the UEs can be naturally cast as a Stackelberg game with one leader (BS) and multiple followers (UEs). Here, for the offered reward, the BS aims at maximizing its utility that is modeled as a function of key federated learning performance metrics such as the number of communication rounds needed to reach a desirable global federated learning model accuracy level. Correspondingly, the UEs will respond to the offered reward by the BS and choose their local strategy (i.e., the selection of CPU-frequency cycle for local computation) to maximize their own benefits. Evaluating the responses from the UEs, the BS will adjust its reward rate, and the process repeats until a desired accuracy level is obtained. To this end, the BS must carefully design an incentive mechanism to influence available UEs for training the global model. In the proposed framework, the sequence of interactions between the BS and the UEs to reach a Stackelberg equilibrium is as follows:

- At the beginning, each rational UE in federated learning submits its best response (i.e., optimal CPU-frequency) to the BS for the offered reward rate, to maximize its local utility function. Specifically, each UE considers the viability of the offered reward rate for their incurred computational and communication costs in federated learning.
- Next, the BS evaluates these responses, thereafter, updates and broadcasts its offered reward rate to the UEs, to maximize its own utility function (i.e., minimizing the overall energy consumption and the learning time) for the learning problem.
- To this end, with the optimal offered reward, the UEs will correspondingly tune their strategy and update response that solves their individual utility maximization problem. Hereafter, the iterative process continues in each round of interaction between the BS and UEs.
- In summary, we follow the best response dynamic algorithm to achieve the Stackelberg equilibrium. For this, with the first-order condition, we first find a unique Nash equilibrium at the lower-level problem (among UEs), and, then, use a backward induction method to solve the upper-level problem (the BS's problem).

C. Performance Evaluation

In this section, we evaluate the performance of our proposed incentive-based federated learning model. We consider three participating UEs having different channel conditions explicitly, and having equal local data size. At each UE, we define the mean square error of the learning problem, i.e., the local relative accuracy metric, as θ. Further, the utility model for UEs is chosen as a concave function in terms of local relative accuracy θ and offered reward from the BS.

In Fig. 3a, the impact of the offered reward rate r on the relative accuracy θ for three UEs is shown. Note that, a smaller value of θ means higher accuracy. An increase in the offered
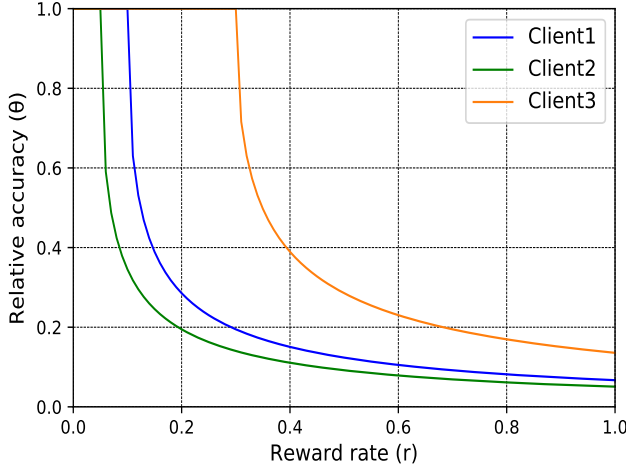
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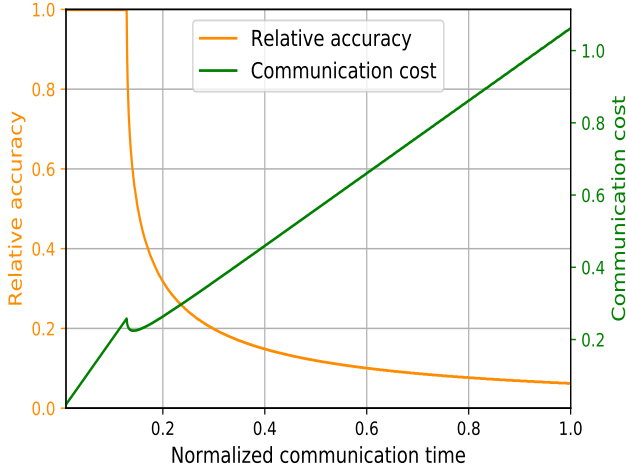
(b)

Fig. 3: Impact of (a) offered reward rate r on client's (UEs) iteration strategy for corresponding relative local accuracy, (b) communication time with relative accuracy.

reward rate will motivate UEs to iterate more within one global iteration, resulting in a lower value of θ, which is intuitive. The heterogeneous responses of UEs is the result of individual computational limitations, local data size, and communication channel conditions. The impact of the communication channel conditions on local relative accuracy for a randomly chosen UE, with defined computational characteristics and local data size is illustrated in Fig. 3 and Fig. 4. For clarity, we use a normalized communication time to quantify the adversity of channel conditions. Here, a unit value for the normalized communication time signifies poor channel conditions. As the normalized communication time increases, we observe that the UEs prefer to iterate more locally to avoid expensive communication costs. Fig. 4 presents the relationship between the offered reward rate and local relative accuracy over the communication cost at a particular UE. The heatmap plot reveals the optimal response behavior for the UEs to maximize the utility function at the given channel conditions. To this
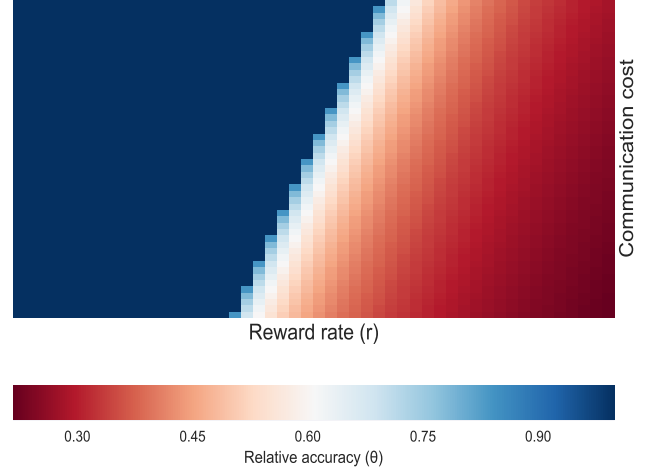

Fig. 4: Impact of offered reward rate, communication cost versus local relative accuracy.

end, we observe heterogeneity in responses of the participating UEs, under different wireless network conditions and due to their local strategies, for the offered incentive to perform federated learning. Thus, it is crucial to have an appropriate incentive design to align responses of the participating UEs for improving the performance of the federated learning model.

IV. OPEN RESEARCH CHALLENGES

A. Resource Optimization for Blockchain based Federated Learning

An attacker might attack the centralized server involved in federated learning in order to alter global model parameters. In addition, a malicious user might alter federated learning parameters during the communication phase. To cope with such security and robustness issues, blockchain based federated learning (BFL) can be used. BFL does not require central coordination in the learning of the global model that results in enhanced robust operation. In BFL, all the users send their local model parameters to their associated miners, which are responsible for sharing local model updates through a distributed ledger. Finally, local model updates of all the devices involved in learning are sent back by miners to their associated devices for the local models aggregation. Although BFL provides benefits of security and robustness, there exist significant challenge of computational and communication resources optimization to reach a consensus among all miners. Static miners can be implemented at the BS, whereas wireless mobile miners can be implemented using unmanned aerial vehicles (UAVs). However, UAVs based mobile miners pose more serious resource allocation challenges than static miners at the BS.

B. Context-Aware Federated Learning

How does one enable more specialized federated learning according to users contextual information? Context-awareness is the ability of a devices/system to sense, understand, and adopt its surrounding environment. To enable intelligent

context-aware applications, federated learning is a viable solution. For instance, consider keyboard search suggestion in smartphones in which the use of federated learning is a promising solution. In such type of design, we must consider context-awareness for enhanced performance. Unique globally shared federated learning model must be used separately for regions with different languages to enable more effective operation. Therefore, the location of the global model must be considered near that region (i.e., micro data center) rather than a central cloud.

C. Mobility-Aware Federated Learning

How does one enable seamless communication of smart mobile devices with an edge server during the learning phase of a global federated learning model? A seamless connectivity of the devices with a centralized server during the training phase must be maintained. Mobility of devices must be considered during the device selection phase of federated learning protocol. Deep learning-based mobility prediction schemes can be used to ensure the connectivity of devices during the training phase of a globally shared global model.

V. CONCLUSIONS AND FUTURE RECOMMENDATIONS

In this paper, we have presented the key design aspects, incentive mechanism, and open research challenges, for enabling federated learning in edge networks. Finally, we present several recommendations for future research:

- Generally, federated learning involves training of a global federated learning model via an exchange of learning model updates between a centralized server and geographically distributed devices. However, wireless devices will have heterogeneous energy and processing power (CPU-cycles/sec) capabilities. Moreover, some of the devices might have noisy local datasets. Therefore, there is a need for novel federated learning protocols that will provide criteria for the selection of a set of local devices having sufficient resources. The selection criteria of the devices must include long-lasting backup power, sufficient memory, accurate data, and higher processing power.

- A set of densely populated devices involved in federated learning might not be able to have real-time access to the edge server located at the BS due to a lack of communication resources. To cope with this challenge, one can develop new federated learning protocols based on socially-aware device-to-device (D2D) communication. Socially-aware D2D communication has an advantage of reusing the occupied bandwidth by other users while protecting them by keeping the interference level below the maximum allowed limit. Initially, multiple clusters based on social relationships and the distance between devices should be created. Then, a cluster head is selected for every cluster based on its highest social relationship with other devices. Within every cluster, a sub-global federated learning model is trained iteratively by exchanging the learning model parameters between the cluster head and its associated devices. Then, the sub-global federated learning model parameters from all the cluster heads are sent to the BS for global federated learning model aggregation. Finally, the global federated learning model parameters are sent back to cluster heads which in turn disseminate the learning model parameters to their associated cluster devices.

- Exchange of learning model updates via blockchain offers enhanced security. However, reaching consensus via traditional consensus algorithms among blockchain nodes can add more latency to the learning time. Therefore, it is recommended to design novel consensus algorithms with low latency.

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